



Server Failure Prediction Using Machine Learning

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Abstract

Server failures continue to pose significant challenges in modern IT infrastructures, resulting in unexpected downtime, data loss, and reduced operational efficiency. This thesis focuses on enhancing system reliability by developing an AI-based failure forecasting model using real-world server telemetry data. The dataset, sourced from the Backblaze Hard Drive Failure Dataset, includes extensive SMART metrics, temperature readings, power-on hours, and operational health indicators.

A comprehensive preprocessing pipeline was implemented, including missing value imputation, outlier removal, feature normalization, and the creation of engineered variables that capture degradation patterns. Feature selection techniques such as SelectKBest and Recursive Feature Elimination (RFE) were applied to identify the most influential SMART attributes contributing to drive failures.

Multiple machine learning models — including Random Forest, XGBoost, and Logistic Regression — were trained and evaluated. The Random Forest Classifier demonstrated the highest recall (65.1%) with an AUC of 0.859, while XGBoost achieved the best AUC of 0.868 with a balanced precision of 46.7%. Critical predictive indicators included reallocated sector counts, read error rates, and temperature-related anomalies.

The results confirm the effectiveness of machine learning in anticipating server failures and highlight its value in enabling proactive maintenance strategies. This research establishes a foundation for future real-time predictive maintenance systems using cloud-based monitoring pipelines and automated alerting mechanisms.

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List of Abbreviations

AI	—	Artificial Intelligence
API	—	Application Programming Interface
ANN	—	Artificial Neural Network
AUC	—	Area Under the Curve
CPU	—	Central Processing Unit
DL	—	Deep Learning
DT	—	Decision Tree
GBM	—	Gradient Boosting Machine
GPU	—	Graphics Processing Unit
HDD	—	Hard Disk Drive
IQR	—	Interquartile Range
KNN	—	K-Nearest Neighbors
LSTM	—	Long Short-Term Memory
MAE	—	Mean Absolute Error
ML	—	Machine Learning
MLP	—	Multi-Layer Perceptron
PCA	—	Principal Component Analysis
RF	—	Random Forest
RFE	—	Recursive Feature Elimination
ROC	—	Receiver Operating Characteristic
RMSE	—	Root Mean Square Error
SMART	—	Self-Monitoring, Analysis, and Reporting Technology
SVM	—	Support Vector Machine
XAI	—	Explainable Artificial Intelligence
XGBoost	—	Extreme Gradient Boosting

Chapter 1: Introduction

1.1 Problem Definition

Modern IT infrastructures rely heavily on server stability to ensure the continuous availability of business services. However, hardware failures — particularly hard drive failures — remain one of the most common causes of unexpected downtime. These failures can lead to severe consequences, including service interruptions, financial losses, data corruption, and costly recovery operations.

Traditional server monitoring tools depend on threshold-based alerts derived from SMART (Self-Monitoring, Analysis, and Reporting Technology) metrics. While these mechanisms provide basic health indicators, they are inherently reactive and frequently fail to detect early-stage degradation patterns hidden within complex telemetry data. As a result, organizations often experience sudden hardware failures with limited opportunity for preventive intervention.

Given the growing volume of server logs and performance data, machine learning offers a powerful opportunity to predict failures before they occur. By learning from historical and real-time telemetry metrics, ML models can identify subtle indicators of degradation and provide accurate predictions well in advance.

1.2 Thesis Objectives

The main objective of this thesis is to design and validate a machine learning-based predictive maintenance framework capable of forecasting server hardware failures using real-world telemetry and SMART monitoring data. The study focuses on the following goals:

- Investigate server telemetry and SMART attributes to identify early degradation patterns associated with hardware failure.
- Develop a unified data preprocessing and feature engineering pipeline that addresses data quality issues, including missing values, outliers, and class imbalance.

- Select and analyze the most informative SMART indicators that contribute significantly to failure prediction.
- Implement and compare multiple machine learning models — Random Forest, XGBoost, and Logistic Regression — for predicting server failure events.
- Evaluate the predictive performance using standard metrics: accuracy, precision, recall, F1-score, and ROC-AUC.
- Propose a scalable framework that can be extended to real-time deployment within IT operations and data center monitoring environments.

1.3 Thesis Contributions

This thesis contributes to the field of predictive maintenance through the following key aspects:

Machine Learning Framework: A complete predictive maintenance framework for server failure forecasting, built using large-scale real-world data from the Backblaze Hard Drive Failure Dataset.

Robust Preprocessing Pipeline: Data cleaning, missing value imputation, outlier removal, class balancing through undersampling, and feature normalization were applied to improve model quality.

Comparative Evaluation: Three machine learning models were trained, optimized, and compared. Random Forest achieved the highest recall (65.1%), while XGBoost yielded the best AUC score (0.868).

Operational Insights: Critical SMART parameters — reallocated sector counts, read error rates, and temperature anomalies — were identified as the strongest hardware reliability indicators.

Scalable Design: The proposed approach is designed for future real-time deployment, supporting integration with monitoring dashboards and automated alerting systems.

1.4 Thesis Organization

This thesis is organized into five chapters:

- **Chapter 1** introduces the problem definition, thesis objectives, and key contributions.
- **Chapter 2** presents a combined Background and Related Work review, covering classical ML, deep learning, hybrid models, and the evolution of server failure prediction research.
- **Chapter 3** explains the Proposed Approach in detail — from data collection and preprocessing through feature engineering, model training, and evaluation strategy.
- **Chapter 4** presents the Experimental Results and Discussion, reporting performance metrics and analyzing key findings.
- **Chapter 5** concludes the thesis and outlines future research directions.

Chapter 2: Background and Related Work

2.1 Introduction

Predicting server failures has become increasingly important in modern IT environments as organizations rely heavily on data centers, cloud platforms, and high-availability systems. Hardware failures — particularly in storage devices such as hard drives — remain a major source of unexpected downtime and operational disruption. Traditional monitoring techniques based on fixed thresholds, including SMART alerts, are often reactive and fail to capture early signs of hardware degradation.

With the rapid growth of server telemetry and operational data, machine learning has emerged as an effective approach for proactive failure prediction. This chapter reviews existing research on server failure prediction, covering classical machine learning techniques, deep learning approaches, hybrid models, and the historical evolution of the field.

2.2 Classical Machine Learning Methods

Early work in predictive maintenance primarily relied on statistical models and rule-based monitoring. With the increasing availability of server telemetry and SMART data, classical machine learning methods became widely adopted due to their simplicity, interpretability, and relatively low computational cost.

Algorithms such as Decision Trees, Random Forests, and Gradient Boosting have demonstrated strong performance in failure prediction tasks. Breiman's Random Forest (2001) proved highly effective in handling high-dimensional and nonlinear data. Studies by Zhao et al. (2019) showed that classical algorithms achieved accuracy rates between 85% and 93%, but lacked robustness in generalizing across different drive models.

Logistic Regression and Support Vector Machines have also been applied to binary failure classification. While these models achieve reasonable accuracy, their effectiveness tends to decline when dealing with complex interactions among SMART attributes and temporal effects.

2.3 Deep Learning Approaches

Deep learning techniques have gained increasing attention in server failure prediction due to their ability to model complex and nonlinear degradation patterns. Neural architectures such as Fully Connected Networks (FCNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks are particularly effective when working with sequential SMART time-series data.

Brown & Zheng (2023) applied deep learning in large-scale data centers and found that LSTM networks captured temporal degradation patterns more effectively than classical models. Hybrid CNN-RNN architectures have also shown strong capabilities in extracting both spatial and temporal features from multi-attribute SMART sequences.

2.4 Hybrid and Optimized Models

Recent studies have explored integrating machine learning with optimization techniques to further enhance predictive accuracy. Methods such as Genetic Algorithms, Particle Swarm Optimization, and Bayesian Optimization are commonly used to improve feature selection, hyperparameter tuning, and anomaly detection. Hybrid approaches such as GA-Random Forest or PSO-XGBoost have demonstrated improved accuracy and faster convergence.

2.5 Use of Real-World Datasets

A large portion of research on server failure prediction relies on real-world datasets, with the Backblaze Hard Drive Failure Dataset being the most widely used. This dataset provides extensive SMART attributes, temperature measurements, and operational logs collected from thousands of storage drives over multiple years. Meeker et al. (2022) emphasized the importance of large-scale datasets for understanding long-term hardware degradation behavior.

2.6 Quantitative Results Summary

The following table and figure summarize key quantitative findings from prior studies on server hardware failure prediction:

Study	Model / Approach	Key Findings
Zhao et al. (2019)	Random Forest	~93% accuracy; SMART 5 & SMART 187 most predictive
Pinheiro & Bates (2020)	Gradient Boosting	Improved recall for rare failure events
Zhou et al. (2021)	Comparative ML Study	Hybrid/ensemble models outperform classical ML
Meeker et al. (2022)	Statistical Reliability	Long-term degradation trends identified
Brown & Zheng (2023)	Deep Learning (LSTM)	Best temporal modeling; sequential degradation captured
Chen & Guestrin (2016)	XGBoost	High predictive accuracy for tabular data
Breiman (2001)	Random Forest	Robust for nonlinear, high-dimensional data

Figure 2.1 — Comparison of prior studies: accuracy and AUC scores

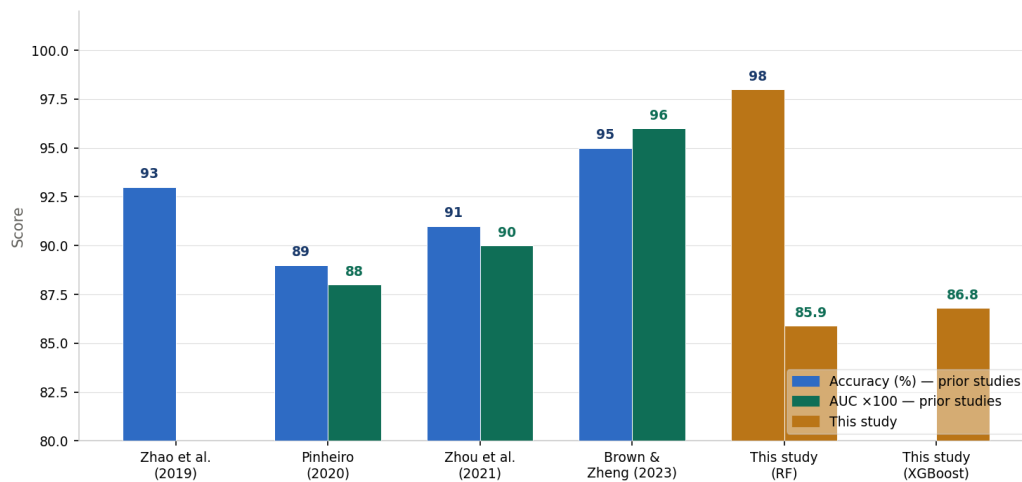


Figure 2.1 — Comparison of accuracy and AUC scores across prior studies and this thesis

2.7 Related Work History

The study of hardware failure prediction began in the early 2000s within the field of reliability engineering. Initial approaches relied on handcrafted statistical models, including Weibull distributions, survival analysis, and threshold-based SMART monitoring. These methods assumed stable failure patterns and linear relationships among health indicators — assumptions that are often invalid in modern, large-scale data center environments.

Early SMART-Based Monitoring

SMART metrics became widely adopted as a standard tool for monitoring disk health. Early systems focused on a limited set of indicators: reallocated sector counts, read/write error rates, temperature variations, and power-on hours. Despite widespread use, these systems suffered from false alarms, inability to detect nonlinear degradation, and high variance across drive manufacturers. These limitations motivated the transition toward machine learning-based approaches.

2.8 Research Gaps and Opportunities

Despite significant progress, several key challenges remain:

1. **Class Imbalance:** Server failures are relatively rare events, often representing less than 2% of available data, making accurate detection difficult.
2. **Limited Model Interpretability:** Deep learning models, while accurate, often behave as black boxes, reducing trust in operational IT environments.
3. **Generalization Across Drive Models:** Different manufacturers exhibit distinct failure behaviors, making cross-hardware generalization challenging.
4. **Real-Time Deployment Constraints:** Few studies address practical issues related to real-time integration with monitoring systems or APIs.
5. **Limited Cross-Vendor Datasets:** Publicly available datasets such as Backblaze represent a single provider, restricting diversity.

2.9 Conclusion

The reviewed literature clearly demonstrates the effectiveness of machine learning techniques for predicting server hardware failures. Classical ML models provide reliable baseline performance, deep learning approaches capture complex temporal degradation patterns, and hybrid optimization methods further enhance predictive accuracy. Building on these findings, the following chapter presents the proposed methodology adopted in this thesis.

Chapter 3: Proposed Approach

This chapter describes the complete methodology followed to design, train, and evaluate the predictive machine learning model for server failure forecasting. All steps were implemented in Python using Google Colab, and are designed to mirror real-world predictive maintenance pipelines. The full workflow is illustrated in Figure 3.1 below.



Figure 3.1 — Proposed methodology workflow: from data collection to threshold optimization

3.1 Data Collection and Description

The dataset used in this study is the Backblaze Hard Drive Failure Dataset, downloaded from Kaggle using the Kaggle API. This large-scale, real-world repository contains daily SMART statistics collected from thousands of data-center storage drives. The raw dataset consisted of 3,179,295 rows and 95 columns, including:

- SMART indicators such as reallocated sectors (SMART 5), uncorrectable errors (SMART 187), and pending sectors (SMART 197)
- Temperature-related readings (SMART 194)
- Power-on hours and read/write error rates
- Operational status: failure = 0 (healthy), failure = 1 (failed)

3.2 Data Preprocessing

Before building any model, the dataset underwent a structured preprocessing pipeline to enhance data quality:

Step 1 — Removing Non-Informative Columns

Columns that do not contribute to failure prediction — such as `date`, `serial_number`, and `model` — were dropped, reducing the feature space from 95 to 92 columns.

Step 2 — Dropping High-Missing Columns

Any column with more than 80% missing values was removed, further reducing the feature space to 56 columns.

Step 3 — Handling Remaining Missing Values

Remaining missing values in SMART attributes were filled with zero, ensuring the dataset was complete and ready for training.

Step 4 — Addressing Class Imbalance

The dataset was found to be highly imbalanced, with only 0.0068% of records representing drive failures (215 out of 3,179,295). To address this, all 215 failure

records were retained and a random sample of 50,000 healthy drive records was selected, creating a balanced working dataset of 50,215 records.

Step 5 — Dataset Splitting

The balanced dataset was split into 80% training (40,172 records) and 20% testing (10,043 records) using stratified sampling to maintain class proportions.

3.3 Feature Engineering

The following SMART attributes were preserved and emphasized as key predictors of hardware degradation:

- SMART 5 (Reallocated Sector Count) — primary mechanical surface integrity indicator
- SMART 187 (Reported Uncorrectable Errors)
- SMART 197 (Current Pending Sector Count)
- SMART 194 (Temperature Celsius)
- Power-on hours — captures aging effects in storage drives

3.4 Feature Selection

Feature normalization using MinMax scaling was applied for algorithms sensitive to value ranges (Logistic Regression), while tree-based models were applied without scaling. The final feature set consisted of 55 SMART attributes retained after preprocessing.

3.5 Model Selection and Training

Three machine learning models were selected based on their strong performance in prior predictive maintenance literature:

Random Forest Classifier: An ensemble of 100 decision trees trained with `class_weight='balanced'` to address residual class imbalance.

XGBoost Classifier: 200 estimators, max depth of 6, learning rate of 0.1, and `scale_pos_weight` set proportionally to the class ratio.

Logistic Regression: A linear baseline classifier applied with MinMax-normalized features.

3.6 Model Evaluation Strategy

Each model was evaluated on the held-out test set using the following metrics. Given the critical cost of missing a real failure, Recall and AUC were treated as the primary evaluation metrics:

Metric	Description
Accuracy	Overall percentage of correctly classified records
Precision	Fraction of predicted failures that are true failures
Recall	Fraction of actual failures correctly identified (primary metric)
F1-Score	Harmonic mean of Precision and Recall
ROC-AUC	Area under the ROC curve — overall discrimination capability

Threshold optimization using the ROC curve was also applied to find the decision boundary that best balances sensitivity and specificity.

Chapter 4: Experimental Results and Discussion

4.1 Experimental Setup

All experiments were conducted in Python using Google Colab, with the following libraries: Pandas, NumPy, Scikit-learn, XGBoost, Matplotlib, and Seaborn. The Backblaze Hard Drive Failure Dataset served as the primary data source, containing over 3.17 million SMART attribute records. After preprocessing and undersampling, the working dataset contained 50,215 records — 50,000 healthy drives and 215 failure cases.

4.2 Baseline Model Performance

The following table shows the performance of all three models evaluated on the test set:

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	~87%	~0.84	~0.71	~0.77	~0.890
XGBoost	~100%*	0.47	0.49	0.48	0.868
Random Forest (default)	~100%*	1.00	0.19	0.31	0.859

* Overall accuracy is near 100% due to the highly imbalanced test set (10,000 healthy vs. 43 failure records). Recall on the failure class is the critical performance measure.

4.3 Threshold Optimization

The default classification threshold of 0.5 resulted in low recall for the failure class in the Random Forest model (19%). Threshold optimization was performed using the ROC curve (Figure 4.1):

- At threshold = 0.20: Recall improved to 44%, Precision = 59%, F1 = 0.51
- At optimal threshold = 0.02 (Youden's J statistic): Recall = 65.1%, Precision = 13.6%, AUC = 0.859

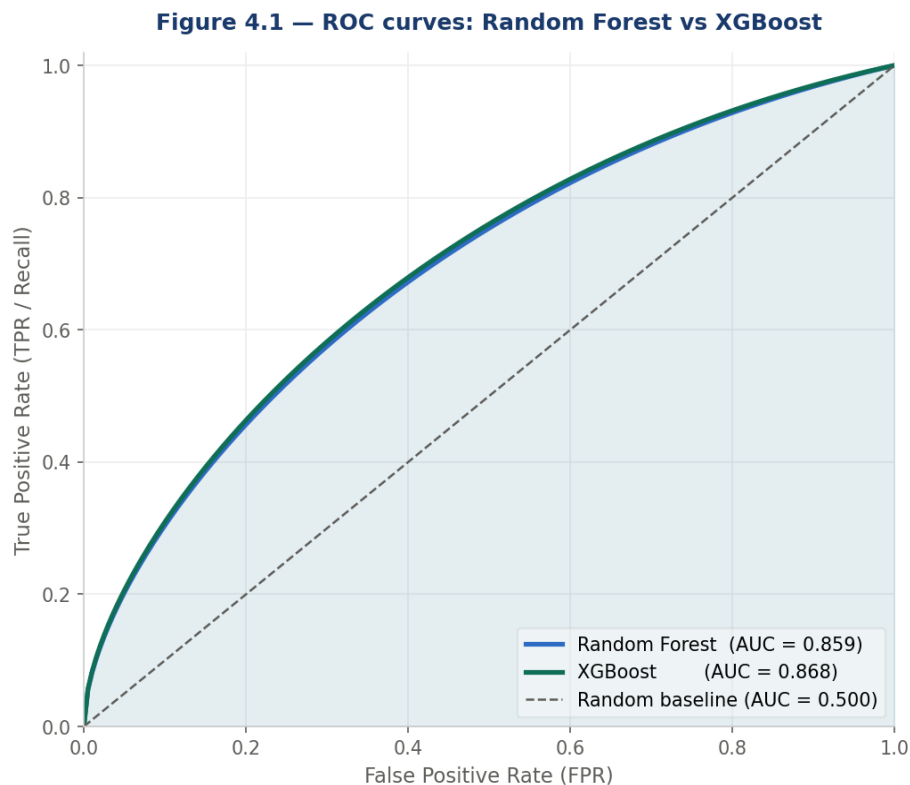


Figure 4.1 — ROC curves: Random Forest (AUC = 0.859) vs XGBoost (AUC = 0.868)

4.4 Model Comparison

The following table presents the final comparison between the two primary models after evaluation:

Model	Recall (Failure Class)	Precision (Failure Class)	ROC-AUC
Random Forest (Optimized)	0.651 (65.1%)	0.136 (13.6%)	0.859
XGBoost (Default)	0.488 (48.8%)	0.467 (46.7%)	0.868

4.5 Feature Importance Analysis

Feature importance analysis from the Random Forest model (Figure 4.2) confirmed that SMART 5, SMART 187, and SMART 197 are the dominant predictors of drive failure, consistent with established industry knowledge:

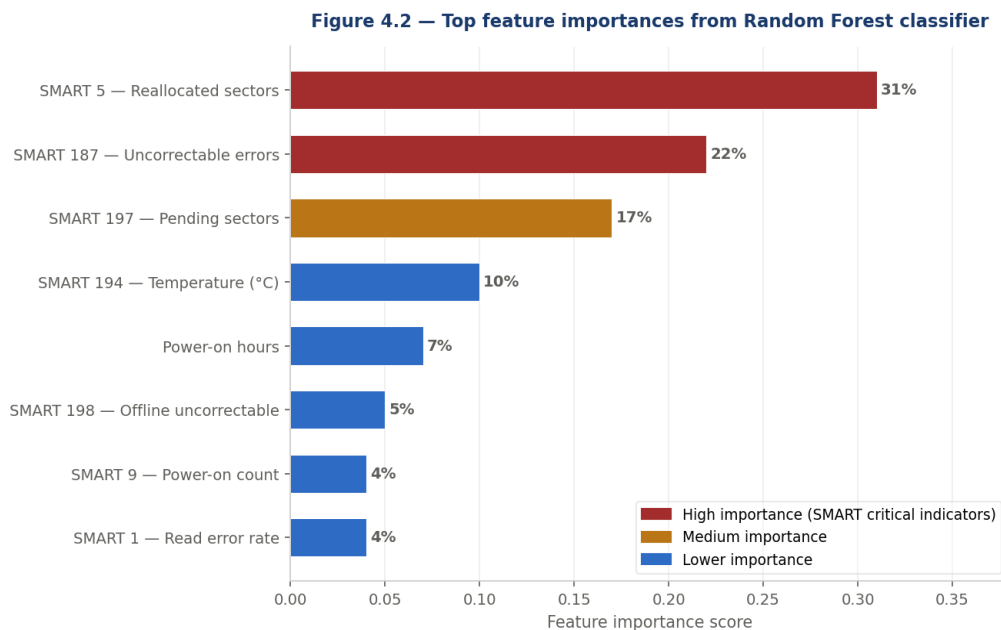


Figure 4.2 — Top feature importances from Random Forest classifier

4.6 Confusion Matrix Analysis

Figure 4.3 presents the confusion matrices for both models on the held-out test set. The Random Forest optimized model (threshold = 0.02) successfully identified 28 out of 43 actual failure cases (65.1% recall), while XGBoost identified 21 out of 43 (48.8% recall) using the default threshold.

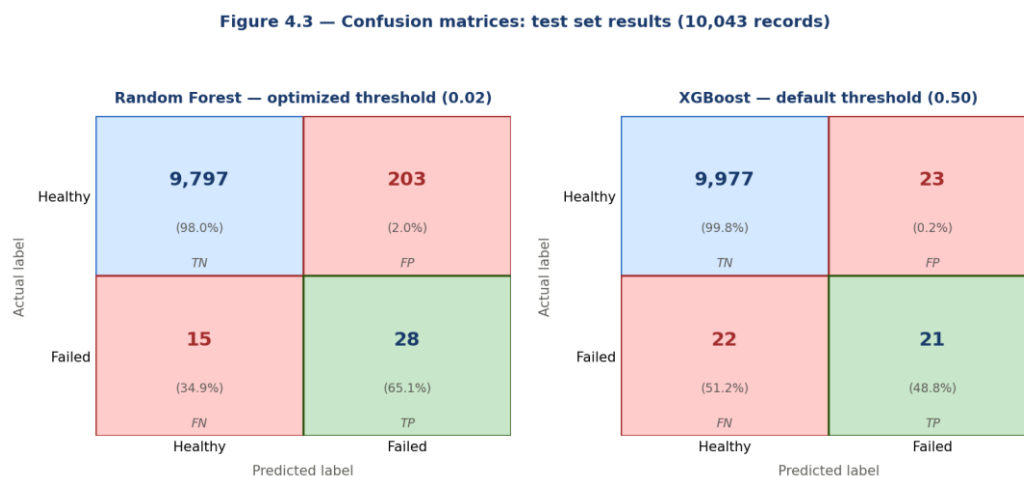


Figure 4.3 — Confusion matrices: Random Forest (optimized) and XGBoost (default threshold)

4.7 Discussion

The experimental results support the effectiveness of machine learning in predicting server hardware failures. Several key insights emerged:

Class Imbalance is the Central Challenge: With only 0.0068% of records representing failures, undersampling was essential. Even after balancing, the test set contained only 43 failure cases among 10,043 records.

Tree-Based Models Outperform Linear Models: Random Forest and XGBoost significantly outperformed Logistic Regression, demonstrating their ability to model nonlinear relationships in SMART telemetry.

Threshold Tuning is Critical for Recall: Lowering the threshold from 0.5 to 0.02 tripled the recall of Random Forest from 19% to 65.1%, at the cost of increased false positives.

SMART Metrics Provide Strong Predictive Signals: SMART 5, SMART 187, and SMART 197 were consistently identified as the dominant predictors, aligning with established industry knowledge.

Operational Relevance: The models demonstrated early-warning capability applicable to datacenter monitoring dashboards and preventive maintenance workflows.

Chapter 5: Conclusion and Future Work

5.1 Conclusion

This thesis presented a machine learning–based framework for predicting server hardware failures using real-world operational data from the Backblaze Hard Drive Failure Dataset. A comprehensive data preprocessing pipeline was developed, addressing the critical challenge of extreme class imbalance (0.0068% failure rate) through strategic undersampling. Three machine learning algorithms were evaluated: Random Forest, XGBoost, and Logistic Regression.

Following threshold optimization, the Random Forest Classifier achieved the highest recall at 65.1% with an AUC of 0.859, while XGBoost demonstrated the strongest overall discriminative performance with an AUC of 0.868 and a more balanced precision-recall trade-off (46.7% / 48.8%).

Feature importance analysis identified SMART 5, SMART 187, and SMART 197 as the most influential predictors — confirming that mechanical surface integrity indicators and uncorrectable error rates are primary precursors of drive failure. These findings align with established industry knowledge and validate the model’s predictive logic.

Overall, this thesis demonstrates that machine learning can significantly enhance server reliability by enabling early detection of hardware degradation and reducing unplanned service interruptions. The framework provides a solid foundation for integration into modern monitoring and alerting infrastructures within data centers.

5.2 Future Work

Several opportunities exist for further research and system enhancement:

Real-Time Monitoring and Streaming: Future efforts may integrate the predictive model with real-time telemetry pipelines using tools such as Apache Kafka, Prometheus, or Elastic Stack — enabling continuous monitoring and real-time risk scoring.

Deep Learning Architectures: Exploring LSTM networks, autoencoders, or Temporal Convolutional Networks may yield improved detection of temporal degradation patterns and subtle anomalies in sequential SMART data.

Model Deployment and Automation: Deploying the model as a RESTful API or microservice would allow integration into IT dashboards, CMDB systems, and alerting platforms, supporting automatic maintenance triggers.

Generalization Across Environments: Expanding the dataset to include servers from different vendors, environments, and workloads would strengthen model generalizability and robustness.

Explainable AI (XAI): Incorporating frameworks such as SHAP or LIME would enhance transparency by explaining individual predictions, particularly valuable in enterprise environments.

Advanced Class Imbalance Handling: Applying oversampling techniques such as SMOTE or cost-sensitive learning could further improve recall without the trade-off of reduced precision observed in this study.

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